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Combining time and mode of interaction

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Investigating physics learning with layered student interaction networks:

Combining time and modes of interaction

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1. Interaction in layered networks

Centrality in student interaction networks (SINs) can be linked to variables like grades [1], persistence [2], and participation [3]. Recent efforts in the field of network science have been done to investigate layered - or multiplex - networks as mathematical objects [4]. These networks can be explored via centrality measures, which then have to be modified to suit layered networks. In student interaction networks [1], a node represents aspects of a student, and links represent aspects of student interactions. Using longitudinal self-reported interactions from Danish university students, this study investigates how target entropy [5,1] and page-rank [6,7] are affected when we take time and modes of interaction into account. We present our preliminary models and results and outline our future work in this area.

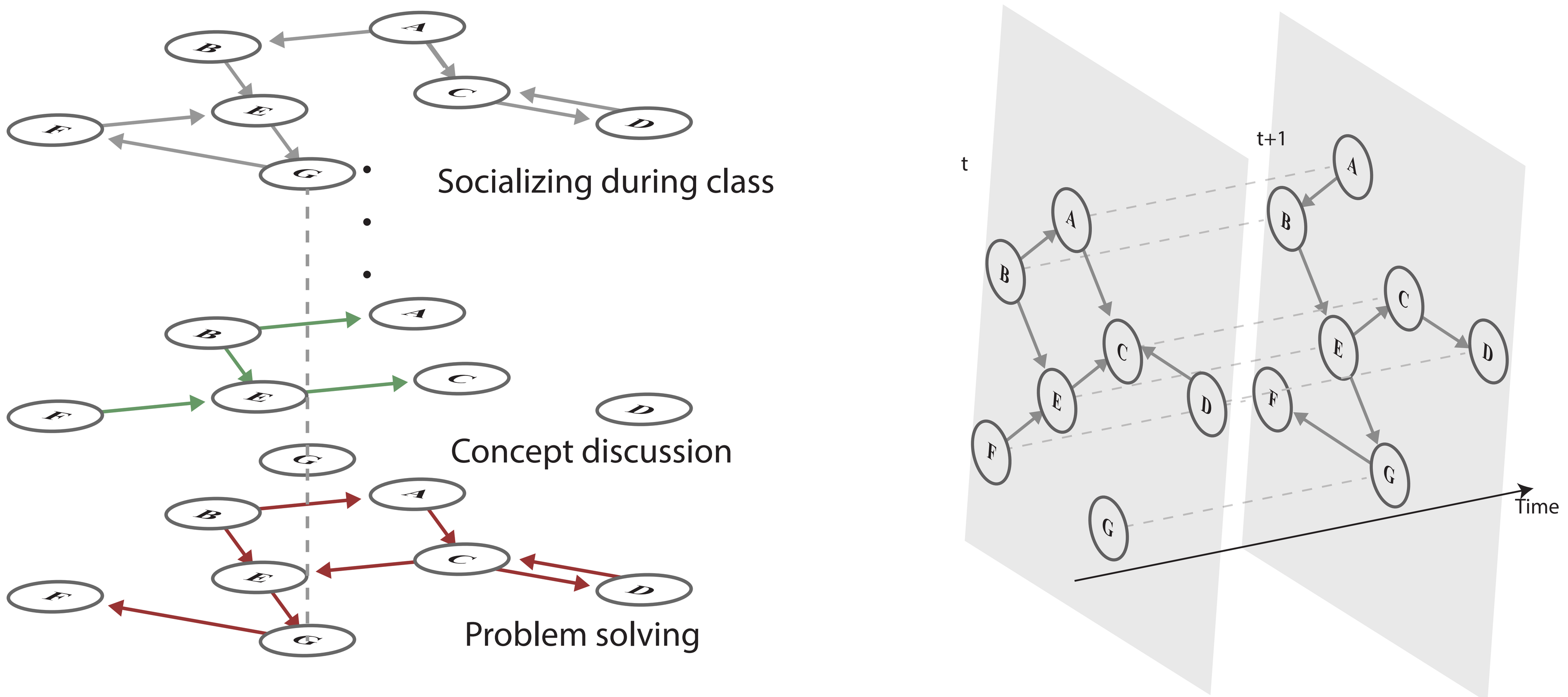

Figure 1: Layered networks. The leftmost figure shows sample student interaction network layers for one week. A student potentially has a presence in each layer depending on the connections in that layer. The rightmost figure shows that layered networks can also be understood as a time sequence.

2. Models of interaction and engagement with categories and time

The analysis is based on *problem solving* (PS) and *concept discussion* (CD) SINs. We use the same dataset as in [1] and focus on PS and CD interactions. For each week, students have indicated with whom they remember having discussed problem solving and concepts in physics respectively.

Pagerank time model and category model
In a layered network, a random walker move both within and between layers [6,7]. The rank of a given node is the percentage of times that node is visited by the random walker.

Layered category networks can be seen to model modelling how individuals may engage with different kinds of knowledge and/or practices.

Layered time networks within a single category allow us to model individuals varying engagement with knowledge and/or practices.

Target entropy time model
Target entropy can be seen to model how likely a student is to engage with, for example, new ideas, new ways of doing og being, or concepts - here modelled as "messages". With our time model, we introduce the idea that a student might not only engage with other students but also has a memory of previous weeks.

Target entropy of node i

$$T_i = \sum_{j \neq i, i_{t-1}} c_{ji} \log_2(c_{ji})$$

Fraction of "messages" from node j to node i

$$c_{ji} = \frac{n_{ji}(t)}{M_i^{tot}(t)}$$

Total "messages" to node i at time t. δ is a memory-effect.

$$\hat{M}_i^{tot}(t) = M_i^{tot}(t) + \delta M_i^{tot}(t-1)$$

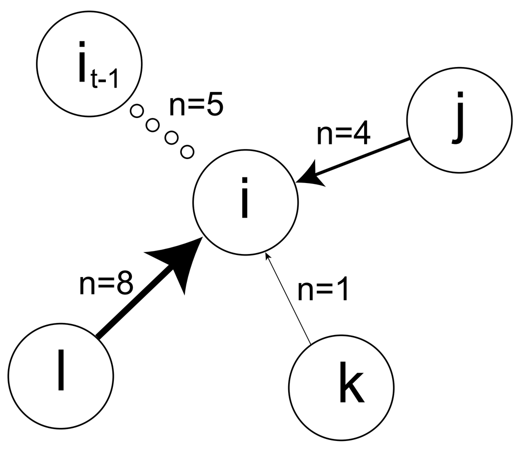

Figure 2: Illustration of our time model for target entropy.

3. Preliminary results and ideas for next steps

We use the correlations pagerank~PS,CD and target entropy~CD [1] as benchmarks. For each model we calculate the layered centralitiy and compare with the corresponding benchmark. We found that PageRank on the agglomorated PS-CD layered network did worse than the benchmark for both CD or PS networks.

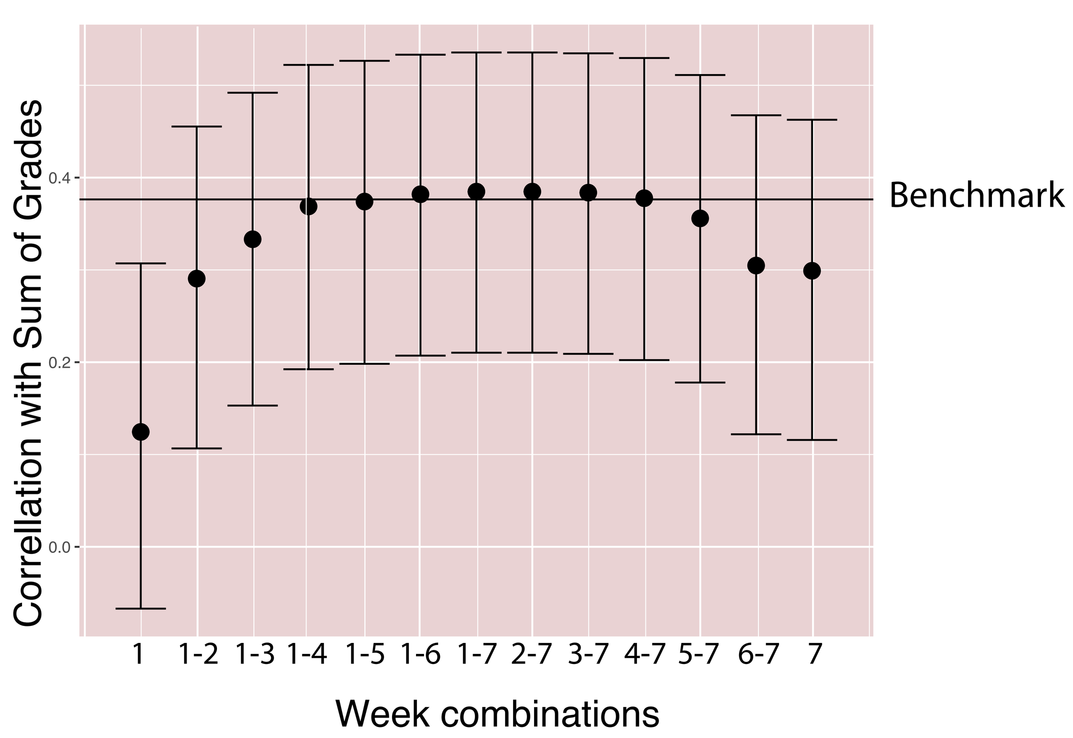

Figure 3: How multilayer pagerank compares to the benchmark for PS SINs.Numbers on x-axis refer to combinations of weeks

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Figure 4: How target entropy time model compares to the benchmark for CD SINs.Numbers on x-axis refer to different settings of parameter δ.

Next steps

- Try out other models and combinations for memory and layered models
- Extend analysis to other cohorts
- Investigate layered networks with respect to student communities
- Use records of of student course completion as they are registered at UCPH

Selected Literature

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